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A modeling framework for optimal energy management of a residential building

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ABSTRACT

Residential buildings are currently equipped with energy production facilities, e.g., solar rooftops and batteries, which in conjunction with smart meters, can function as smart energy hubs coordinating the loads and the resources in an optimal manner. This paper presents a mathematical model for the optimal energy management of a residential building and proposes a centralized energy management system (CEMS) framework for off-grid operation. The model of each component of the hub is integrated within the CEMS. The optimal decisions are determined in real-time by considering these models with realistic parameter settings and customer preferences. Model predictive control (MPC) is used to adapt the optimal decisions on a receding horizon to account for the deviations in the system inputs. Simulation results are presented to demonstrate the feasibility and effectiveness of the proposed CEMS framework. Results show that the proposed CEMS can reduce the energy cost and energy consumption of the customers by approximately 17% and 8%, respectively, over a day. Using the proposed CEMS, the total charging cycles of the ESS were reduced by more than 50% in a day.

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1. Introduction

The U.S. Department of Energy Microgrid Exchange Group defines microgrid as a group of interconnected loads and distributed energy resources (DERs) within clearly identified electrical boundaries that act as a single controllable entity with respect to the grid. A microgrid can connect and disconnect from the grid and operate in both grid-connected or island-modes, respectively. While grid-connected microgrids have the advantage that the grid acts as a supply reservoir to balance the demand when needed, such a facility is not available for an isolated microgrid. The isolated microgrids are constrained by the generation capacity available within the microgrid only, and are expected to rely on various controllable and intermittent resources to match and balance the demand supply gap. Therefore, energy management in isolated microgrids is a much more challenging problem [1]. A residential building with typical loads, and DERs such as distributed generators (DGs), storage devices, controllable loads, etc., can be considered a microgrid that can be operated in a controlled and coordinated manner either connected to the grid or in an islanded mode.

Significant efforts are being made by researchers to develop intelligent control algorithms integrated with information technology to manage energy consumption and thereby regulate load growth. Demand response (DR) programs are being implemented by utilities and Local Distribution Companies (LDCs) to alter the load shape in response to price signals or operator requests during critical conditions. DR is defined by the Federal Energy Regulatory Commission (FERC) in [2] as: “Changes in electricity use by demand-side resources from their normal consumption patterns in response to changes in the price of electricity, or to incentive payments designed to induce lower electricity use at time of high wholesale market price or when system reliability is jeopardized.” These programs help the LDC to maintain a fairly uniform load level, thereby reducing its need for new supply resources or feeders.

Although DR has taken center-stage in the context of smart grids, demand-side management (DSM) programs have been in existence and practice for several decades now [3]. For example, the authors in [4] state that one way to reduce costs is to use direct utility-consumer communications to implement a “load follow supply” concept. In such a system, the customer’s demand

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Nomenclature

Indices

k	time sample (every 15 min), k =1,2,. . .,96

Parameters

η_{chg}, η_{dchg}	charging and discharging efficiency, respectively [p.u.]
η_{MPPT}	efficiency of PV's DC/DC converter
τ	time interval [h]
φ	self discharge rate [p.u.]
C	equivalent heat capacity [J/°C]
C_1, C_2	cost of the ESS related to discharging power [$/W] and charging cycles [$/CYC], respectively
$\overline{E}$	rated energy capacity of ESS [kWh]
G	irradiation on the device surface, $G = 1000\,\mathrm{W/m^2}$
L_m, L_h	energy loss associated with medium and high charging/discharging rate [p.u.]
$\overline{P}_{chg}, \overline{P}_{dchg}$	maximum power drawn and supplied by the ESS, respectively [W]
P_{Dem}	base load profile of a building [W]
$\underline{P}_{gen}, \overline{P}_{gen}$	minimum and maximum power output of diesel generator, respectively [W]
$\overline{P}_{grid}$	maximum power that can be purchase from the grid [W]
P_{hvac}	rated power of HVAC unit [W]
P_{pv}, P_{pv}^{rated}	output power and rated power of solar PV, respectively [W]
Q, R	equivalent heat rate [W] and thermal resistance [°C/W], respectively
R_l, R_m, R_h	charging/discharging of the ESS at low, medium, and high rate, respectively [W]
RUP, RDN	ramp-up and ramp-down limit of diesel generator, respectively [W]
$\underline{SOC}, \overline{SOC}$	initial and final state of charge of the ESS, respectively [p.u.]
T^{out}	outside temperature [Celsius]
$\underline{T}, \overline{T}$	upper and lower bounds of temperature [Celsius]

Variables

C_{ess}, C_{gen}	operating cost of ESS and diesel generator, respectively [$]
C_l, C_m, C_h	binary variable to check charging level status of ESS: low/medium/high, respectively
CYC	total number of charging cycles [p.u.]
D_l, D_m, D_h	binary variable to check discharging level status of ESS: low/medium/high, respectively
E_{bat}	energy of the ESS [Wh]
J	objective function value [$]
P_{chg}, P_{dchg}	power drawn and supplied by the ESS, respectively [W]
P_{grid}	power purchased from grid [W]
P_{gen}	output power of a diesel generator [W]
S_k, S^{ht}	status [ON/OFF] of diesel generator and HVAC unit, respectively
SOC	state of charge of the ESS [p.u.]
T	inside temperature of the building [Celsius]
u	binary variable to check when new charging cycle starts
u_1, u_2	binary variable associated with charging and discharging of ESS, respectively

would be controlled through interruption of power for specific uses. DSM programs encourage customers to be more energy efficient which can be achieved by shifting the demand from peak hours to mid-peak or off-peak hours; reducing energy consumption; and consuming locally produced energy [5–7].

It has been shown in [8] that up to 30% energy savings can be brought about in a residential building by optimizing the operation and management of the building's energy system without changing the building structure or hardware configuration of its energy supply system. There is a potential for improving the building's energy efficiency by optimal operation of the various energy sources and controllable loads. Rooftop solar photo-voltaic (PV) generation, energy storage system (ESS), DG and controllable loads can be considered as a part of a residential building in a smart grid. However, in order to achieve the desired objective, all microgrid assets, local generation resources, storage devices and controllable loads, need be integrated into a proper control and management system.

The optimal energy management problem in microgrids has been extensively investigated in the literature [8–13]. To solve a dispatch problem for microgrids, meta-heuristic and heuristic techniques, such as genetic algorithms, evolutionary algorithms, particle swarm optimization, and Tabu search have been proposed by researchers [14]. In [10], a coordinated control approach for microgrid energy management was proposed that comprised a scheduling and a dispatch layer. The optimal integrated scheduling and control of building energy supply resources was considered in [8] with the objective to minimize the overall cost of electricity and natural gas consumption and significant energy cost savings were obtained.

In [11], a model for optimal operation of a microgrid is proposed; the problem is decomposed into a grid-connected operation master problem and an islanded operation subproblem. The scheduling decisions are revised based on islanding cuts that ensured sufficient generation was available to guarantee a feasible island, which were further revised to dispatch the generating units, ESS and controllable loads. In [15], a generalized formulation smart energy management of a microgrid was proposed with a multi-objective function that sought to minimize the operating cost and the environmental impacts taking into account the uncertainty of the exogenous variables and forecasted inputs.

A probabilistic approach was proposed in [12] to analyze a microgrid's operational performance considering uncertainties in solar PV, ESS and conventional generators. A microgrid operations model was proposed in [13] where load curtailment was minimized by efficiently scheduling the available resources when power from the main grid was interrupted for an extended period of time. All the above studies discussed, are from the perspective of the grid, while behavior of an individual customer has not been considered. In the context of smart grids where customers are equipped with local energy production resources and controllable loads, it is important to study their load behavior as it may affect the operating decisions of a microgrid/grid. Thus, in this paper, the proposed centralized energy management system (CEMS) focuses on determining the load profile of a building which can help utilities/microgrids operate in a reliable, safe, and cost effective manner.

Lot of work has been reported on energy management in buildings, cost optimal strategies, and energy consumption forecast [16–23]. In [23], the thermal behavior of a building equipped with energy production and storage facility is modeled. Two strategies are considered i.e., managing solar PV and wind; and managing solar PV, wind and ESS; results show that by shifting the loads from peak hours to off-peak hours can bring about a reduction in energy costs. However, uncertainty due to weather and energy demand is not considered in this work. In [24], a control algorithm is proposed that uses hot water storage tanks to simultaneously dispatch the heating and electrical devices. In another work on energy management [25], a predictive controller is implemented with centralized